Coursera - Practical Machine Learning Project

LOFOR ANDREW

7 May,2019

Background

Using devices such as Jawbone Up, Nike FuelBand, and Fitbit it is now possible to collect a large amount of data about personal activity relatively inexpensively. These type of devices are part of the quantified self movement – a group of enthusiasts who take measurements about themselves regularly to improve their health, to find patterns in their behavior, or because they are tech geeks. One thing that people regularly do is quantify how much of a particular activity they do, but they rarely quantify how well they do it.

In this project, your goal will be to use data from accelerometers on the belt, forearm, arm, and dumbell of 6 participants. They were asked to perform barbell lifts correctly and incorrectly in 5 different ways. More information is available from the website here: http://groupware.les.inf.puc-rio.br/har (see the section on the Weight Lifting Exercise Dataset).

Libraries

```
library(caret)
```

```
## Warning: package 'caret' was built under R version 3.3.2

## Loading required package: lattice

## Warning: package 'lattice' was built under R version 3.3.2

## Loading required package: ggplot2

## Warning: package 'ggplot2' was built under R version 3.3.2
```

```
library(rattle)
```

```
## Warning: package 'rattle' was built under R version 3.3.2

## Rattle : une interface graphique gratuite pour l'exploration de données av
ec R.

## Version 4.1.0 Copyright (c) 2006-2015 Togaware Pty Ltd.

## Entrez 'rattle()' pour secouer, faire vibrer, et faire défiler vos données
.
```

Data load

```r
TrainData <- read.csv(url("https://d396qusza40orc.cloudfront.net/predmachlear
n/pml-training.csv"),header=TRUE)

dim(TrainData)
```

```
## [1] 19622   160
```

```r
TestData <- read.csv(url("https://d396qusza40orc.cloudfront.net/predmachlearn
/pml-testing.csv"),header=TRUE)

dim(TestData)
```

```
## [1]  20 160
```

```r
str(TrainData)
```

```
## 'data.frame':    19622 obs. of  160 variables:

##  $ X                        : int  1 2 3 4 5 6 7 8 9 10 ...

##  $ user_name                : Factor w/ 6 levels "adelmo","carlitos",..: 2
2 2 2 2 2 2 2 2 2 ...

##  $ raw_timestamp_part_1     : int  1323084231 1323084231 1323084231 1323084
232 1323084232 1323084232 1323084232 1323084232 1323084232 1323084232 ...

##  $ raw_timestamp_part_2     : int  788290 808298 820366 120339 196328 30427
7 368296 440390 484323 484434 ...

##  $ cvtd_timestamp           : Factor w/ 20 levels "02/12/2011 13:32",..: 9
9 9 9 9 9 9 9 9 9 ...

##  $ new_window               : Factor w/ 2 levels "no","yes": 1 1 1 1 1 1 1
1 1 1 ...

##  $ num_window               : int  11 11 11 12 12 12 12 12 12 12 ...

##  $ roll_belt                : num  1.41 1.41 1.42 1.48 1.48 1.45 1.42 1.42
1.43 1.45 ...

##  $ pitch_belt               : num  8.07 8.07 8.07 8.05 8.07 8.06 8.09 8.13
8.16 8.17 ...

##  $ yaw_belt                 : num  -94.4 -94.4 -94.4 -94.4 -94.4 -94.4 -94.
4 -94.4 -94.4 -94.4 ...

##  $ total_accel_belt         : int  3 3 3 3 3 3 3 3 3 3 ...

##  $ kurtosis_roll_belt       : Factor w/ 397 levels "","-0.016850",..: 1 1 1
1 1 1 1 1 1 1 ...

##  $ kurtosis_picth_belt      : Factor w/ 317 levels "","-0.021887",..: 1 1 1
1 1 1 1 1 1 1 ...

##  $ kurtosis_yaw_belt        : Factor w/ 2 levels "","#DIV/0!": 1 1 1 1 1 1
1 1 1 1 ...

##  $ skewness_roll_belt       : Factor w/ 395 levels "","-0.003095",..: 1 1 1
1 1 1 1 1 1 1 ...

##  $ skewness_roll_belt.1     : Factor w/ 338 levels "","-0.005928",..: 1 1 1
1 1 1 1 1 1 1 ...
```

```
##  $ skewness_yaw_belt       : Factor w/ 2 levels "","#DIV/0!": 1 1 1 1 1 1
1 1 1 1 ...
##  $ max_roll_belt           : num  NA NA NA NA NA NA NA NA NA NA ...
##  $ max_picth_belt          : int  NA NA NA NA NA NA NA NA NA NA ...
##  $ max_yaw_belt            : Factor w/ 68 levels "","-0.1","-0.2",..: 1 1
1 1 1 1 1 1 1 1 ...
##  $ min_roll_belt           : num  NA NA NA NA NA NA NA NA NA NA ...
##  $ min_pitch_belt          : int  NA NA NA NA NA NA NA NA NA NA ...
##  $ min_yaw_belt            : Factor w/ 68 levels "","-0.1","-0.2",..: 1 1
1 1 1 1 1 1 1 1 ...
##  $ amplitude_roll_belt     : num  NA NA NA NA NA NA NA NA NA NA ...
##  $ amplitude_pitch_belt    : int  NA NA NA NA NA NA NA NA NA NA ...
##  $ amplitude_yaw_belt      : Factor w/ 4 levels "","#DIV/0!","0.00",..: 1
1 1 1 1 1 1 1 1 1 ...
##  $ var_total_accel_belt    : num  NA NA NA NA NA NA NA NA NA NA ...
##  $ avg_roll_belt           : num  NA NA NA NA NA NA NA NA NA NA ...
##  $ stddev_roll_belt        : num  NA NA NA NA NA NA NA NA NA NA ...
##  $ var_roll_belt           : num  NA NA NA NA NA NA NA NA NA NA ...
##  $ avg_pitch_belt          : num  NA NA NA NA NA NA NA NA NA NA ...
##  $ stddev_pitch_belt       : num  NA NA NA NA NA NA NA NA NA NA ...
##  $ var_pitch_belt          : num  NA NA NA NA NA NA NA NA NA NA ...
##  $ avg_yaw_belt            : num  NA NA NA NA NA NA NA NA NA NA ...
##  $ stddev_yaw_belt         : num  NA NA NA NA NA NA NA NA NA NA ...
##  $ var_yaw_belt            : num  NA NA NA NA NA NA NA NA NA NA ...
##  $ gyros_belt_x            : num  0 0.02 0 0.02 0.02 0.02 0.02 0.02 0.02 0
.03 ...
##  $ gyros_belt_y            : num  0 0 0 0 0.02 0 0 0 0 0 ...
##  $ gyros_belt_z            : num  -0.02 -0.02 -0.02 -0.03 -0.02 -0.02 -0.0
2 -0.02 -0.02 0 ...
##  $ accel_belt_x            : int  -21 -22 -20 -22 -21 -21 -22 -22 -20 -21
...
##  $ accel_belt_y            : int  4 4 5 3 2 4 3 4 2 4 ...
##  $ accel_belt_z            : int  22 22 23 21 24 21 21 21 24 22 ...
##  $ magnet_belt_x           : int  -3 -7 -2 -6 -6 0 -4 -2 1 -3 ...
##  $ magnet_belt_y           : int  599 608 600 604 600 603 599 603 602 609
...
##  $ magnet_belt_z           : int  -313 -311 -305 -310 -302 -312 -311 -313
-312 -308 ...
```

```
##  $ roll_arm                : num  -128 -128 -128 -128 -128 -128 -128 -128
-128 -128 ...
##  $ pitch_arm               : num  22.5 22.5 22.5 22.1 22.1 22 21.9 21.8 21
.7 21.6 ...
##  $ yaw_arm                 : num  -161 -161 -161 -161 -161 -161 -161 -161
-161 -161 ...
##  $ total_accel_arm         : int  34 34 34 34 34 34 34 34 34 34 ...
##  $ var_accel_arm           : num  NA NA NA NA NA NA NA NA NA NA ...
##  $ avg_roll_arm            : num  NA NA NA NA NA NA NA NA NA NA ...
##  $ stddev_roll_arm         : num  NA NA NA NA NA NA NA NA NA NA ...
##  $ var_roll_arm            : num  NA NA NA NA NA NA NA NA NA NA ...
##  $ avg_pitch_arm           : num  NA NA NA NA NA NA NA NA NA NA ...
##  $ stddev_pitch_arm        : num  NA NA NA NA NA NA NA NA NA NA ...
##  $ var_pitch_arm           : num  NA NA NA NA NA NA NA NA NA NA ...
##  $ avg_yaw_arm             : num  NA NA NA NA NA NA NA NA NA NA ...
##  $ stddev_yaw_arm          : num  NA NA NA NA NA NA NA NA NA NA ...
##  $ var_yaw_arm             : num  NA NA NA NA NA NA NA NA NA NA ...
##  $ gyros_arm_x             : num  0 0.02 0.02 0.02 0 0.02 0 0.02 0.02 0.02
...
##  $ gyros_arm_y             : num  0 -0.02 -0.02 -0.03 -0.03 -0.03 -0.03 -0
.02 -0.03 -0.03 ...
##  $ gyros_arm_z             : num  -0.02 -0.02 -0.02 0.02 0 0 0 0 -0.02 -0.
02 ...
##  $ accel_arm_x             : int  -288 -290 -289 -289 -289 -289 -289 -289
-288 -288 ...
##  $ accel_arm_y             : int  109 110 110 111 111 111 111 111 109 110
...
##  $ accel_arm_z             : int  -123 -125 -126 -123 -123 -122 -125 -124
-122 -124 ...
##  $ magnet_arm_x            : int  -368 -369 -368 -372 -374 -369 -373 -372
-369 -376 ...
##  $ magnet_arm_y            : int  337 337 344 344 337 342 336 338 341 334
...
##  $ magnet_arm_z            : int  516 513 513 512 506 513 509 510 518 516
...
##  $ kurtosis_roll_arm       : Factor w/ 330 levels "","-0.02438",..: 1 1 1
1 1 1 1 1 1 1 ...
##  $ kurtosis_picth_arm      : Factor w/ 328 levels "","-0.00484",..: 1 1 1
1 1 1 1 1 1 1 ...
```

```
##  $ kurtosis_yaw_arm        : Factor w/ 395 levels "","-0.01548",..: 1 1 1
1 1 1 1 1 1 1 ...
##  $ skewness_roll_arm       : Factor w/ 331 levels "","-0.00051",..: 1 1 1
1 1 1 1 1 1 1 ...
##  $ skewness_pitch_arm      : Factor w/ 328 levels "","-0.00184",..: 1 1 1
1 1 1 1 1 1 1 ...
##  $ skewness_yaw_arm        : Factor w/ 395 levels "","-0.00311",..: 1 1 1
1 1 1 1 1 1 1 ...
##  $ max_roll_arm            : num  NA NA NA NA NA NA NA NA NA NA ...
##  $ max_picth_arm           : num  NA NA NA NA NA NA NA NA NA NA ...
##  $ max_yaw_arm             : int  NA NA NA NA NA NA NA NA NA NA ...
##  $ min_roll_arm            : num  NA NA NA NA NA NA NA NA NA NA ...
##  $ min_pitch_arm           : num  NA NA NA NA NA NA NA NA NA NA ...
##  $ min_yaw_arm             : int  NA NA NA NA NA NA NA NA NA NA ...
##  $ amplitude_roll_arm      : num  NA NA NA NA NA NA NA NA NA NA ...
##  $ amplitude_pitch_arm     : num  NA NA NA NA NA NA NA NA NA NA ...
##  $ amplitude_yaw_arm       : int  NA NA NA NA NA NA NA NA NA NA ...
##  $ roll_dumbbell           : num  13.1 13.1 12.9 13.4 13.4 ...
##  $ pitch_dumbbell          : num  -70.5 -70.6 -70.3 -70.4 -70.4 ...
##  $ yaw_dumbbell            : num  -84.9 -84.7 -85.1 -84.9 -84.9 ...
##  $ kurtosis_roll_dumbbell  : Factor w/ 398 levels "","-0.0035","-0.0073",.
.: 1 1 1 1 1 1 1 1 1 1 ...
##  $ kurtosis_picth_dumbbell : Factor w/ 401 levels "","-0.0163","-0.0233",.
.: 1 1 1 1 1 1 1 1 1 1 ...
##  $ kurtosis_yaw_dumbbell   : Factor w/ 2 levels "","#DIV/0!": 1 1 1 1 1 1
1 1 1 1 ...
##  $ skewness_roll_dumbbell  : Factor w/ 401 levels "","-0.0082","-0.0096",.
.: 1 1 1 1 1 1 1 1 1 1 ...
##  $ skewness_pitch_dumbbell : Factor w/ 402 levels "","-0.0053","-0.0084",.
.: 1 1 1 1 1 1 1 1 1 1 ...
##  $ skewness_yaw_dumbbell   : Factor w/ 2 levels "","#DIV/0!": 1 1 1 1 1 1
1 1 1 1 ...
##  $ max_roll_dumbbell       : num  NA NA NA NA NA NA NA NA NA NA ...
##  $ max_picth_dumbbell      : num  NA NA NA NA NA NA NA NA NA NA ...
##  $ max_yaw_dumbbell        : Factor w/ 73 levels "","-0.1","-0.2",..: 1 1
1 1 1 1 1 1 1 1 ...
##  $ min_roll_dumbbell       : num  NA NA NA NA NA NA NA NA NA NA ...
##  $ min_pitch_dumbbell      : num  NA NA NA NA NA NA NA NA NA NA ...
```

```
##  $ min_yaw_dumbbell        : Factor w/ 73 levels "","-0.1","-0.2",..: 1 1
1 1 1 1 1 1 1 1 ...

##  $ amplitude_roll_dumbbell : num  NA NA NA NA NA NA NA NA NA NA ...

##   [list output truncated]
```

The training data set is made of 19622 observations on 160 columns. We can notice that many columns have NA values or blank values on almost every observation. So we will remove them, because they will not produce any information. The first seven columns give information about the people who did the test, and also timestamps. We will not take them in our model.

```
# Here we get the indexes of the columns having at least 90% of NA or blank v
alues on the training dataset

indColToRemove <- which(colSums(is.na(TrainData) |TrainData=="")>0.9*dim(Trai
nData)[1])

TrainDataClean <- TrainData[,-indColToRemove]

TrainDataClean <- TrainDataClean[,-c(1:7)]

dim(TrainDataClean)
```

```
## [1] 19622    53
```

```
# We do the same for the test set

indColToRemove <- which(colSums(is.na(TestData) |TestData=="")>0.9*dim(TestDa
ta)[1])

TestDataClean <- TestData[,-indColToRemove]

TestDataClean <- TestDataClean[,-1]

dim(TestDataClean)
```

```
## [1] 20 59
```

```
str(TestDataClean)
```

```
## 'data.frame':    20 obs. of  59 variables:

##  $ user_name           : Factor w/ 6 levels "adelmo","carlitos",..: 6 5 5
1 4 5 5 5 2 3 ...

##  $ raw_timestamp_part_1: int  1323095002 1322673067 1322673075 1322832789
1322489635 1322673149 1322673128 1322673076 1323084240 1322837822 ...

##  $ raw_timestamp_part_2: int  868349 778725 342967 560311 814776 510661 76
6645 54671 916313 384285 ...

##  $ cvtd_timestamp      : Factor w/ 11 levels "02/12/2011 13:33",..: 5 10 1
0 1 6 11 11 10 3 2 ...

##  $ new_window          : Factor w/ 1 level "no": 1 1 1 1 1 1 1 1 1 1 ...

##  $ num_window          : int  74 431 439 194 235 504 485 440 323 664 ...

##  $ roll_belt           : num  123 1.02 0.87 125 1.35 -5.92 1.2 0.43 0.93 1
14 ...

##  $ pitch_belt          : num  27 4.87 1.82 -41.6 3.33 1.59 4.44 4.15 6.72
22.4 ...
```

```
##  $ yaw_belt            : num  -4.75 -88.9 -88.5 162 -88.6 -87.7 -87.3 -88.
5 -93.7 -13.1 ...
##  $ total_accel_belt    : int  20 4 5 17 3 4 4 4 4 18 ...
##  $ gyros_belt_x        : num  -0.5 -0.06 0.05 0.11 0.03 0.1 -0.06 -0.18 0.
1 0.14 ...
##  $ gyros_belt_y        : num  -0.02 -0.02 0.02 0.11 0.02 0.05 0 -0.02 0 0.
11 ...
##  $ gyros_belt_z        : num  -0.46 -0.07 0.03 -0.16 0 -0.13 0 -0.03 -0.02
-0.16 ...
##  $ accel_belt_x        : int  -38 -13 1 46 -8 -11 -14 -10 -15 -25 ...
##  $ accel_belt_y        : int  69 11 -1 45 4 -16 2 -2 1 63 ...
##  $ accel_belt_z        : int  -179 39 49 -156 27 38 35 42 32 -158 ...
##  $ magnet_belt_x       : int  -13 43 29 169 33 31 50 39 -6 10 ...
##  $ magnet_belt_y       : int  581 636 631 608 566 638 622 635 600 601 ...
##  $ magnet_belt_z       : int  -382 -309 -312 -304 -418 -291 -315 -305 -302
-330 ...
##  $ roll_arm            : num  40.7 0 0 -109 76.1 0 0 0 -137 -82.4 ...
##  $ pitch_arm           : num  -27.8 0 0 55 2.76 0 0 0 11.2 -63.8 ...
##  $ yaw_arm             : num  178 0 0 -142 102 0 0 0 -167 -75.3 ...
##  $ total_accel_arm     : int  10 38 44 25 29 14 15 22 34 32 ...
##  $ gyros_arm_x         : num  -1.65 -1.17 2.1 0.22 -1.96 0.02 2.36 -3.71 0
.03 0.26 ...
##  $ gyros_arm_y         : num  0.48 0.85 -1.36 -0.51 0.79 0.05 -1.01 1.85 -
0.02 -0.5 ...
##  $ gyros_arm_z         : num  -0.18 -0.43 1.13 0.92 -0.54 -0.07 0.89 -0.69
-0.02 0.79 ...
##  $ accel_arm_x         : int  16 -290 -341 -238 -197 -26 99 -98 -287 -301
...
##  $ accel_arm_y         : int  38 215 245 -57 200 130 79 175 111 -42 ...
##  $ accel_arm_z         : int  93 -90 -87 6 -30 -19 -67 -78 -122 -80 ...
##  $ magnet_arm_x        : int  -326 -325 -264 -173 -170 396 702 535 -367 -4
20 ...
##  $ magnet_arm_y        : int  385 447 474 257 275 176 15 215 335 294 ...
##  $ magnet_arm_z        : int  481 434 413 633 617 516 217 385 520 493 ...
##  $ roll_dumbbell       : num  -17.7 54.5 57.1 43.1 -101.4 ...
##  $ pitch_dumbbell      : num  25 -53.7 -51.4 -30 -53.4 ...
##  $ yaw_dumbbell        : num  126.2 -75.5 -75.2 -103.3 -14.2 ...
##  $ total_accel_dumbbell: int  9 31 29 18 4 29 29 29 3 2 ...
```

```
##  $ gyros_dumbbell_x    : num  0.64 0.34 0.39 0.1 0.29 -0.59 0.34 0.37 0.03
0.42 ...
##  $ gyros_dumbbell_y    : num  0.06 0.05 0.14 -0.02 -0.47 0.8 0.16 0.14 -0.
21 0.51 ...
##  $ gyros_dumbbell_z    : num  -0.61 -0.71 -0.34 0.05 -0.46 1.1 -0.23 -0.39
-0.21 -0.03 ...
##  $ accel_dumbbell_x    : int  21 -153 -141 -51 -18 -138 -145 -140 0 -7 ...
##  $ accel_dumbbell_y    : int  -15 155 155 72 -30 166 150 159 25 -20 ...
##  $ accel_dumbbell_z    : int  81 -205 -196 -148 -5 -186 -190 -191 9 7 ...
##  $ magnet_dumbbell_x   : int  523 -502 -506 -576 -424 -543 -484 -515 -519
-531 ...
##  $ magnet_dumbbell_y   : int  -528 388 349 238 252 262 354 350 348 321 ...
##  $ magnet_dumbbell_z   : int  -56 -36 41 53 312 96 97 53 -32 -164 ...
##  $ roll_forearm        : num  141 109 131 0 -176 150 155 -161 15.5 13.2 ..
.
##  $ pitch_forearm       : num  49.3 -17.6 -32.6 0 -2.16 1.46 34.5 43.6 -63.
5 19.4 ...
##  $ yaw_forearm         : num  156 106 93 0 -47.9 89.7 152 -89.5 -139 -105
...
##  $ total_accel_forearm : int  33 39 34 43 24 43 32 47 36 24 ...
##  $ gyros_forearm_x     : num  0.74 1.12 0.18 1.38 -0.75 -0.88 -0.53 0.63 0
.03 0.02 ...
##  $ gyros_forearm_y     : num  -3.34 -2.78 -0.79 0.69 3.1 4.26 1.8 -0.74 0.
02 0.13 ...
##  $ gyros_forearm_z     : num  -0.59 -0.18 0.28 1.8 0.8 1.35 0.75 0.49 -0.0
2 -0.07 ...
##  $ accel_forearm_x     : int  -110 212 154 -92 131 230 -192 -151 195 -212
...
##  $ accel_forearm_y     : int  267 297 271 406 -93 322 170 -331 204 98 ...
##  $ accel_forearm_z     : int  -149 -118 -129 -39 172 -144 -175 -282 -217 -
7 ...
##  $ magnet_forearm_x    : int  -714 -237 -51 -233 375 -300 -678 -109 0 -403
...
##  $ magnet_forearm_y    : int  419 791 698 783 -787 800 284 -619 652 723 ..
.
##  $ magnet_forearm_z    : int  617 873 783 521 91 884 585 -32 469 512 ...
##  $ problem_id          : int  1 2 3 4 5 6 7 8 9 10 ...
```

After cleaning, the new training data set has only 53 columns.

```
# Here we create a partition of the traning data set
```

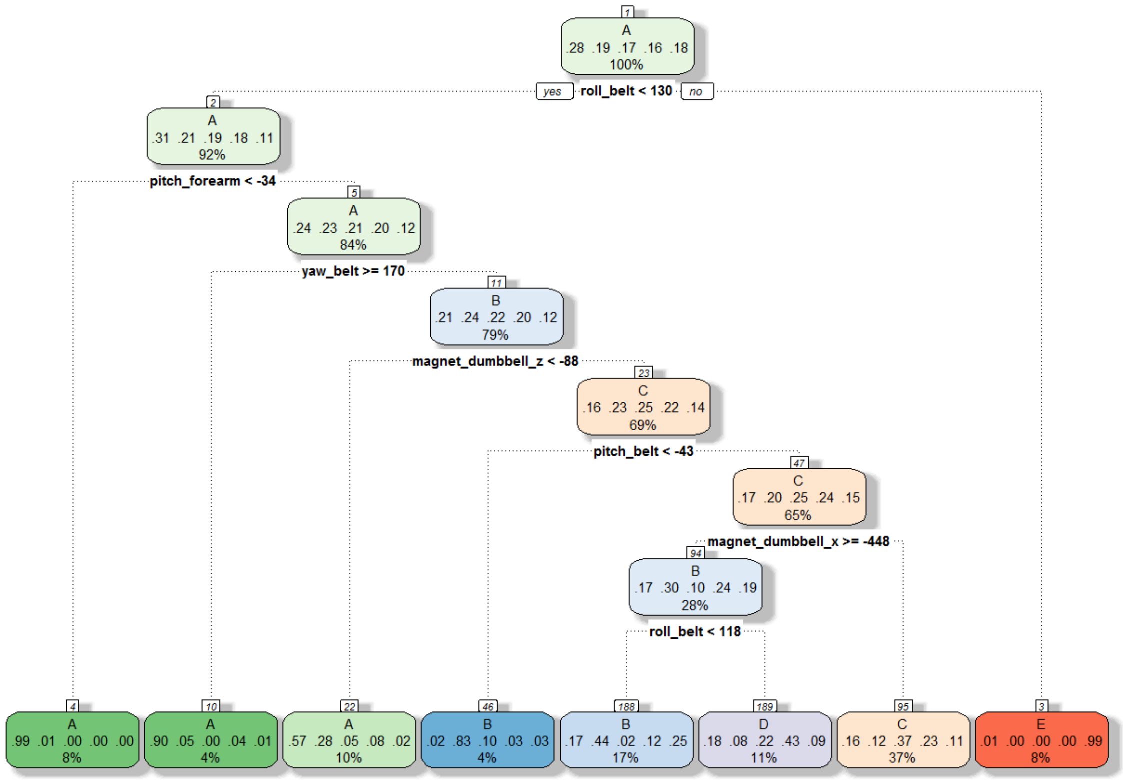
```
set.seed(12345)
inTrain1 <- createDataPartition(TrainDataClean$classe, p=0.75, list=FALSE)
Train1 <- TrainDataClean[inTrain1,]
Test1 <- TrainDataClean[-inTrain1,]
dim(Train1)
## [1] 14718    53
dim(Test1)
## [1] 4904   53
```

In the following sections, we will test 3 different models : * classification tree * random forest * gradient boosting method

In order to limit the effects of overfitting, and improve the efficicency of the models, we will use the ***cross-validation** technique. We will use 5 folds (usually, 5 or 10 can be used, but 10 folds gives higher run times with no significant increase of the accuracy).

Train with classification tree

```
trControl <- trainControl(method="cv", number=5)
model_CT <- train(classe~., data=Train1, method="rpart", trControl=trControl)
## Loading required package: rpart
## Warning: package 'rpart' was built under R version 3.3.2
#print(model_CT)
fancyRpartPlot(model_CT$finalModel)
```



Rattle 2017-janv.-29 19:45:11 Jean-Luc

```
trainpred <- predict(model_CT,newdata=Test1)

confMatCT <- confusionMatrix(Test1$classe,trainpred)

# display confusion matrix and model accuracy
confMatCT$table
```

```
##             Reference
## Prediction   A   B   C   D   E
##          A 870 159 273  88   5
##          B 162 530 214  43   0
##          C  29  36 674 116   0
##          D  46 136 429 193   0
##          E  16 221 224  51 389
```

```
confMatCT$overall[1]
```

```
##  Accuracy
```

```
## 0.5415987
```

We can notice that the accuracy of this first model is very low (about 55%). This means that the outcome class will not be predicted very well by the other predictors.

Train with random forests

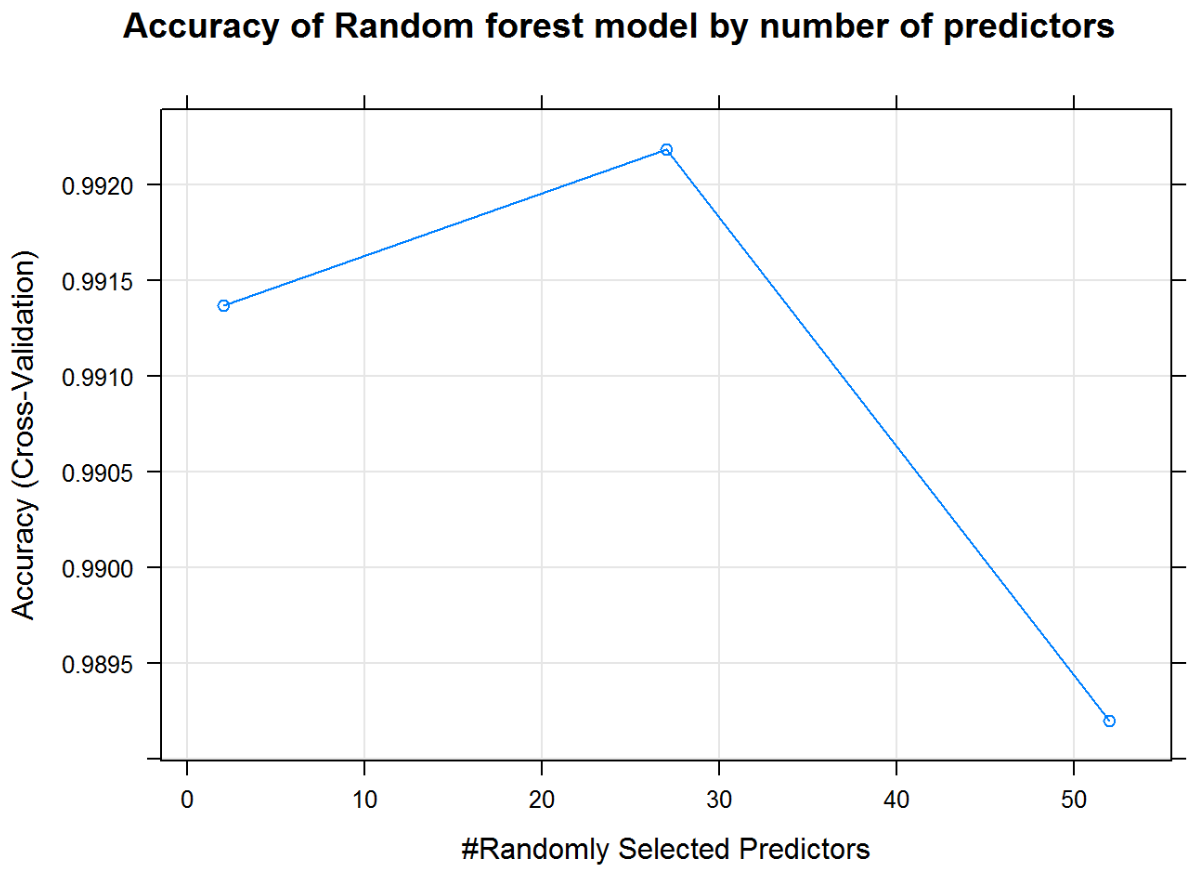
```r
model_RF <- train(classe~., data=Train1, method="rf", trControl=trControl, ve
rbose=FALSE)
```

```
## Loading required package: randomForest
## Warning: package 'randomForest' was built under R version 3.3.2
## randomForest 4.6-12
## Type rfNews() to see new features/changes/bug fixes.
##
## Attaching package: 'randomForest'
## The following object is masked from 'package:ggplot2':
##
##     margin
```

```r
print(model_RF)
```

```
## Random Forest
##
## 14718 samples
##    52 predictor
##     5 classes: 'A', 'B', 'C', 'D', 'E'
##
## No pre-processing
## Resampling: Cross-Validated (5 fold)
## Summary of sample sizes: 11776, 11776, 11774, 11773, 11773
## Resampling results across tuning parameters:
##
##   mtry  Accuracy   Kappa
##    2    0.9913715  0.9890843
##   27    0.9921863  0.9901160
##   52    0.9891966  0.9863337
##
## Accuracy was used to select the optimal model using  the largest value.
```

```
## The final value used for the model was mtry = 27.
plot(model_RF,main="Accuracy of Random forest model by number of predictors")
```




```
trainpred <- predict(model_RF,newdata=Test1)

confMatRF <- confusionMatrix(Test1$classe,trainpred)

# display confusion matrix and model accuracy
confMatRF$table
##           Reference
## Prediction    A    B    C    D    E
##          A 1395    0    0    0    0
##          B    6  939    4    0    0
##          C    0    2  849    4    0
##          D    0    0   11  793    0
##          E    0    0    2    5  894
```

```r
confMatRF$overall[1]
```

```
##  Accuracy 
## 0.9930669
```

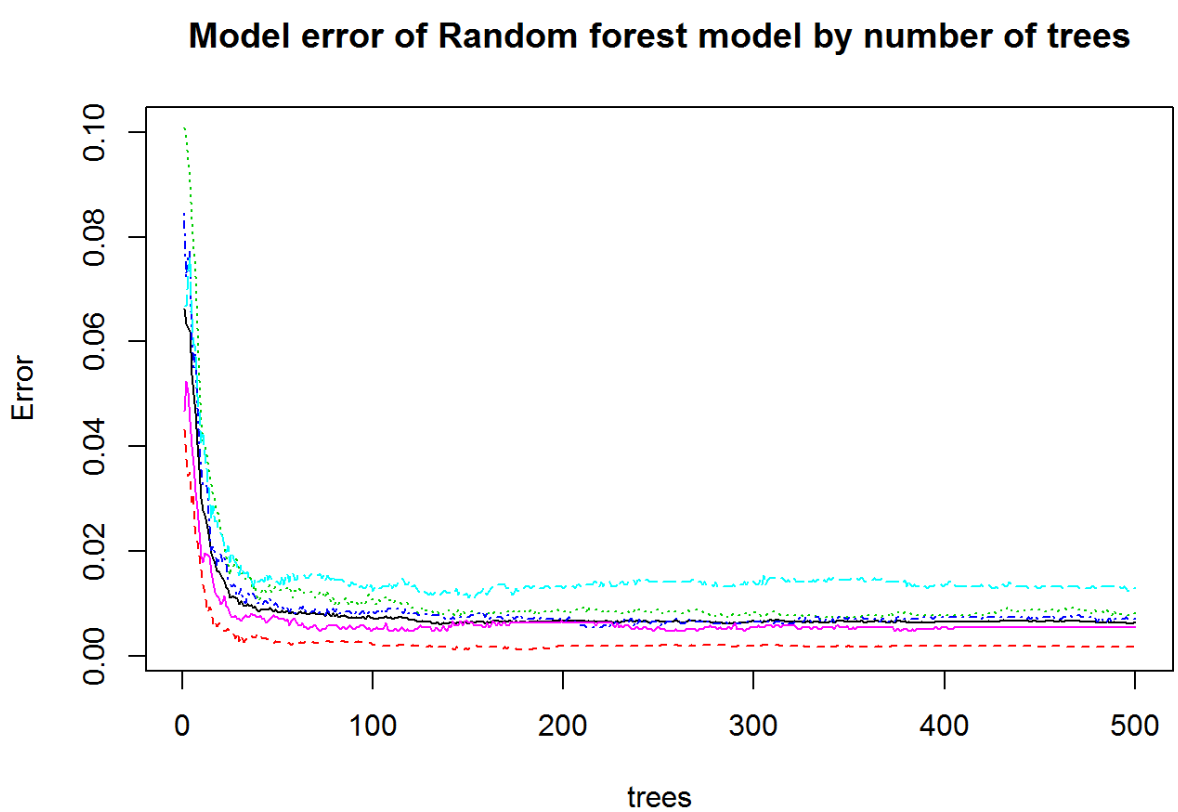
```r
names(model_RF$finalModel)
```

```
##  [1] "call"            "type"            "predicted"      
##  [4] "err.rate"        "confusion"       "votes"          
##  [7] "oob.times"       "classes"         "importance"     
## [10] "importanceSD"    "localImportance" "proximity"      
## [13] "ntree"           "mtry"            "forest"         
## [16] "y"               "test"            "inbag"          
## [19] "xNames"          "problemType"     "tuneValue"      
## [22] "obsLevels"
```

```r
model_RF$finalModel$classes
```

```
## [1] "A" "B" "C" "D" "E"
```

```r
plot(model_RF$finalModel,main="Model error of Random forest model by number o
f trees")
```



```r
# Compute the variable importance
MostImpVars <- varImp(model_RF)
MostImpVars
```

```
## rf variable importance
##
##   only 20 most important variables shown (out of 52)
##
##                      Overall
## roll_belt             100.00
## pitch_forearm          58.88
## yaw_belt               57.19
## magnet_dumbbell_z      44.11
## pitch_belt             43.90
## magnet_dumbbell_y      41.36
## roll_forearm           39.75
## accel_dumbbell_y       21.74
## magnet_dumbbell_x      18.26
## roll_dumbbell          17.90
## accel_forearm_x        17.04
## magnet_belt_z          15.16
## accel_dumbbell_z       15.01
## accel_belt_z           13.94
## magnet_forearm_z       13.86
## total_accel_dumbbell   12.18
## magnet_belt_y          12.03
## yaw_arm                10.65
## gyros_belt_z           10.49
## magnet_belt_x          10.15
```

With random forest, we reach an accuracy of 99.3% using cross-validation with 5 steps. This is very good. But let’s see what we can expect with Gradient boosting.

We can also notice that the optimal number of predictors, i.e. the number of predictors giving the highest accuracy, is 27. There is no significal increase of the accuracy with 2 predictors and 27, but the slope decreases more with more than 27 predictors (even if the accuracy is still very good). The fact that not all the accuracy is worse with all the available predictors lets us suggest that there may be some dependencies between them.

At last, using more than about 30 trees does not reduce the error significantly.

Train with gradient boosting method

```
model_GBM <- train(classe~., data=Train1, method="gbm", trControl=trControl,
verbose=FALSE)
```

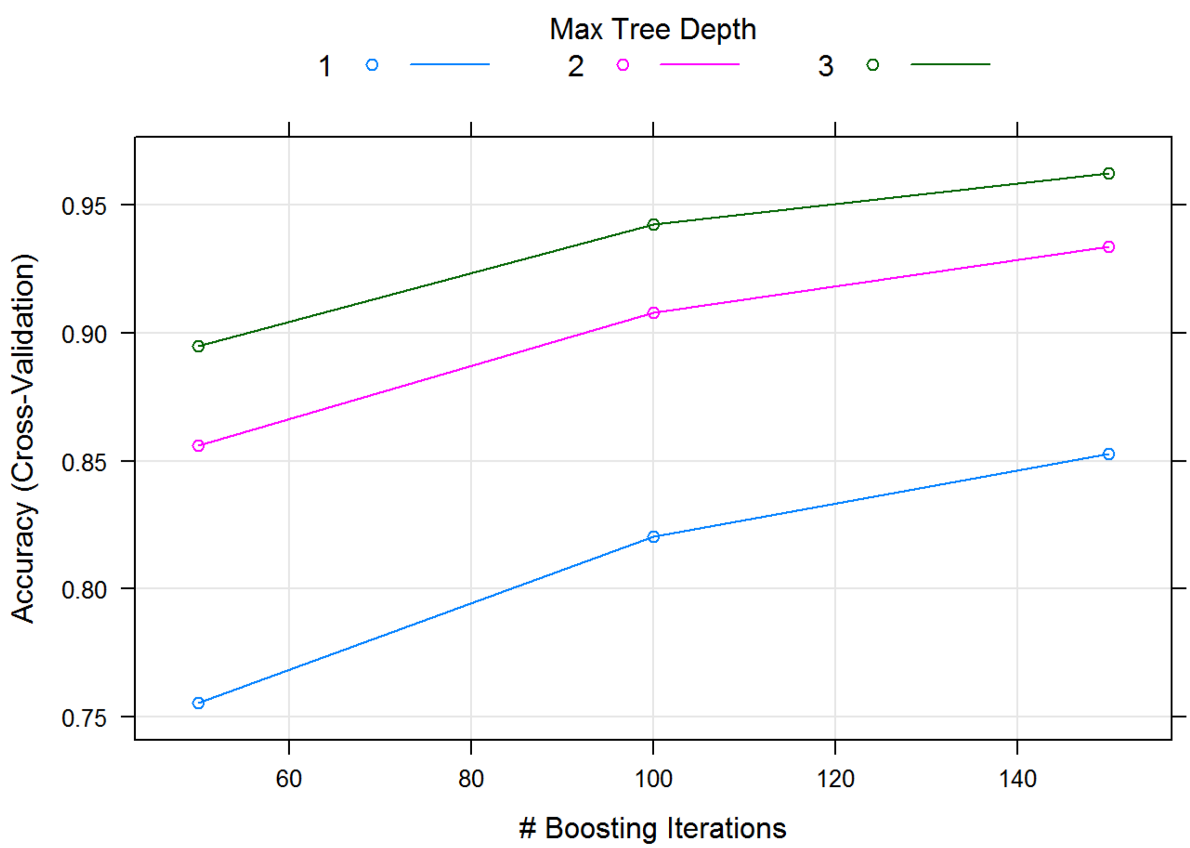
```
## Loading required package: gbm
## Warning: package 'gbm' was built under R version 3.3.2
## Loading required package: survival
## Warning: package 'survival' was built under R version 3.3.2
##
## Attaching package: 'survival'
## The following object is masked from 'package:caret':
##
##     cluster
## Loading required package: splines
## Loading required package: parallel
## Loaded gbm 2.1.1
## Loading required package: plyr
```

```
print(model_GBM)
```

```
## Stochastic Gradient Boosting
##
## 14718 samples
##    52 predictor
##     5 classes: 'A', 'B', 'C', 'D', 'E'
##
## No pre-processing
## Resampling: Cross-Validated (5 fold)
## Summary of sample sizes: 11774, 11773, 11775, 11775, 11775
## Resampling results across tuning parameters:
##
##   interaction.depth  n.trees  Accuracy   Kappa
##   1                   50      0.7553347  0.6900457
##   1                  100      0.8203562  0.7726604
##   1                  150      0.8529006  0.8138884
```

```
##   2                     50      0.8559578  0.8175124
##   2                    100      0.9078676  0.8833875
##   2                    150      0.9338901  0.9163391
##   3                     50      0.8950262  0.8671154
##   3                    100      0.9424506  0.9271793
##   3                    150      0.9623592  0.9523768
##
## Tuning parameter 'shrinkage' was held constant at a value of 0.1
##
## Tuning parameter 'n.minobsinnode' was held constant at a value of 10
## Accuracy was used to select the optimal model using  the largest value.
## The final values used for the model were n.trees = 150,
##  interaction.depth = 3, shrinkage = 0.1 and n.minobsinnode = 10.
```

```
plot(model_GBM)
```




```
trainpred <- predict(model_GBM,newdata=Test1)
```

```
confMatGBM <- confusionMatrix(Test1$classe,trainpred)
confMatGBM$table
##            Reference
## Prediction    A    B    C    D    E
##          A 1377   13    5    0    0
##          B   42  874   30    3    0
##          C    0   16  824   13    2
##          D    0    4   32  765    3
##          E    3   10   10   15  863
confMatGBM$overall[1]
##  Accuracy
## 0.9590131
```

Precision with 5 folds is 95.9%.

Conclusion

This shows that the random forest model is the best one. We will then use it to predict the values of classe for the test data set.

```
FinalTestPred <- predict(model_RF,newdata=TestDataClean)
FinalTestPred
##  [1] B A B A A E D B A A B C B A E E A B B B
## Levels: A B C D E
```